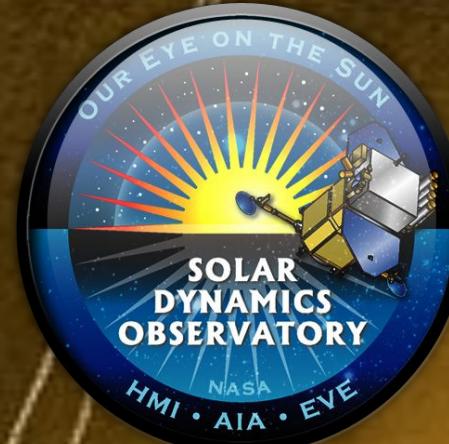


# Auto-Calibration and High-Fidelity Virtual Observations of Remote Sensing Solar Telescopes with Deep Learning

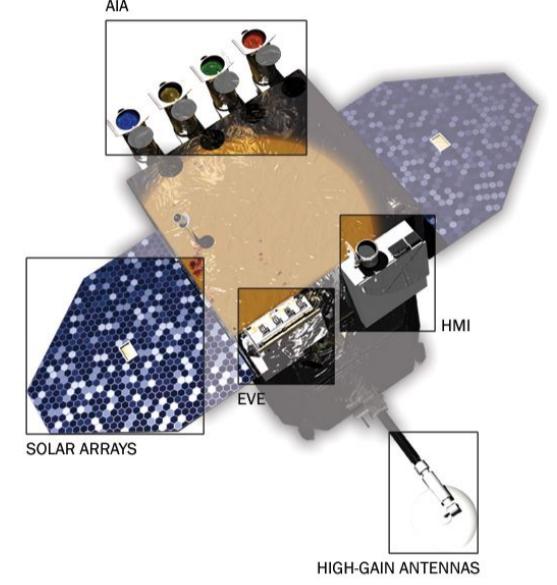


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## BACKGROUND

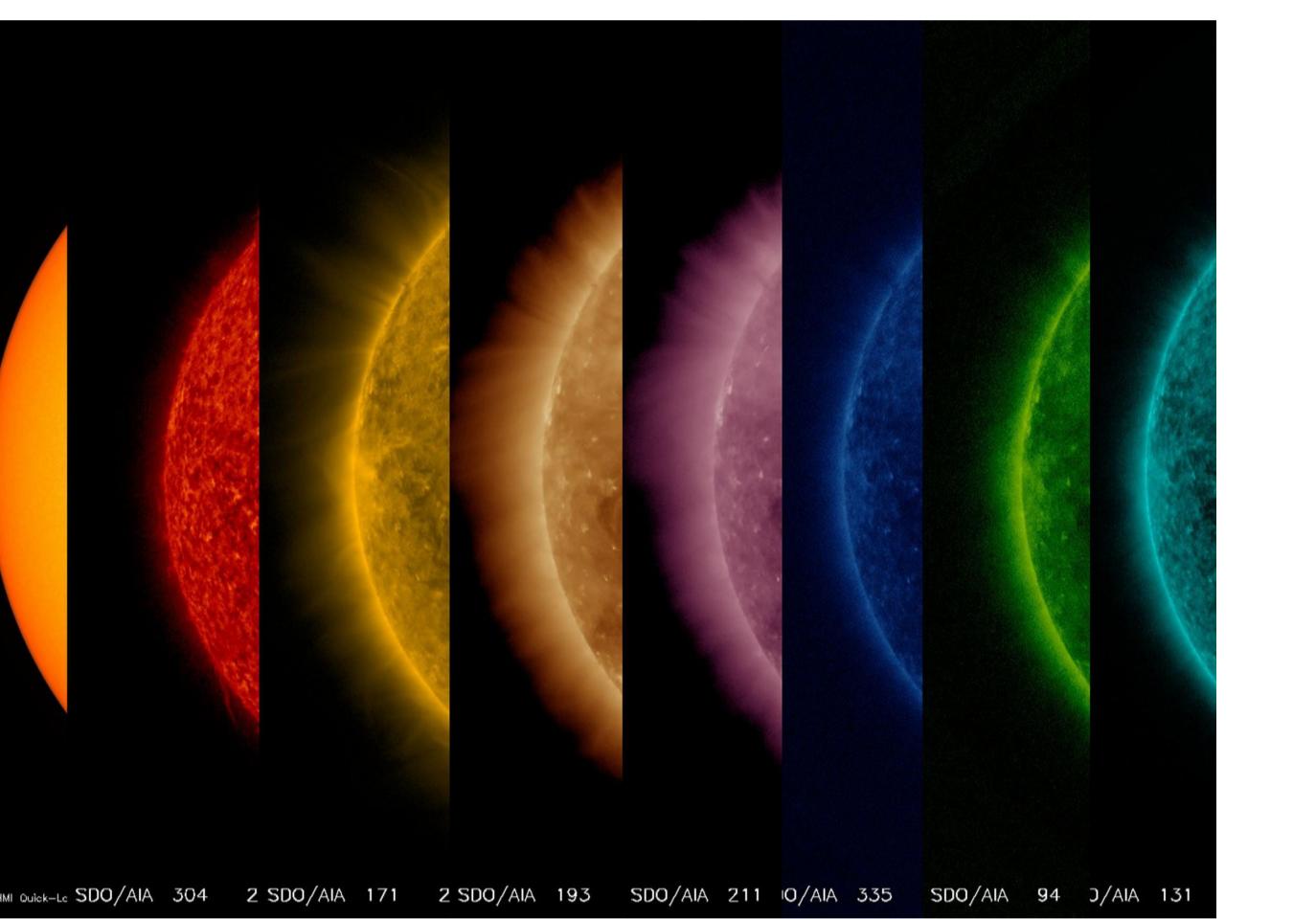


The **Solar Dynamics Observatory (SDO)** [1] is a mission designed to understand the causes of solar variability and its impact on Earth. SDO has been constantly monitoring the Sun 24x7 since 2010, with a 12 second cadence and 4k x 4k resolution, generating **terabytes** of observational data every day.

The **Atmospheric Imaging Assembly (AIA)** [2], one of SDO's instruments, has been collecting full-disk images of the solar atmosphere in 2 UV channels and in 7 extreme UV (EUV) channels with a high temporal and spatial resolution.

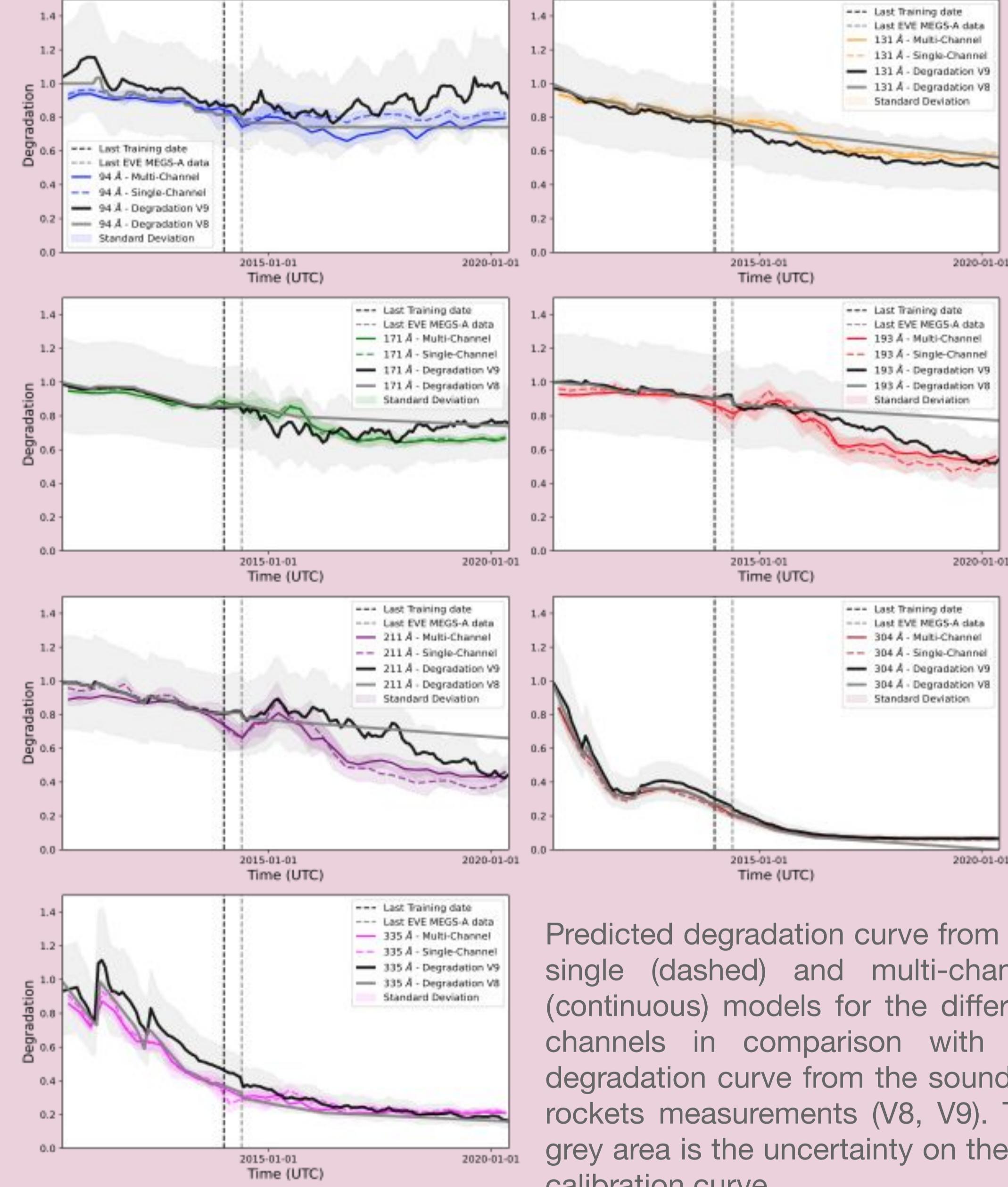
We experimented on how deep learning techniques applied to AIA multi-channel image data can be used to enhance the capabilities of present and future heliophysics missions, particularly in deep-space.

The results refer to two separate experiments: **A - automatic correction of the instrument degradation ; B - synthesis of virtual observations (aimed at reducing telemetry, and potentially hardware, needs of future missions).**



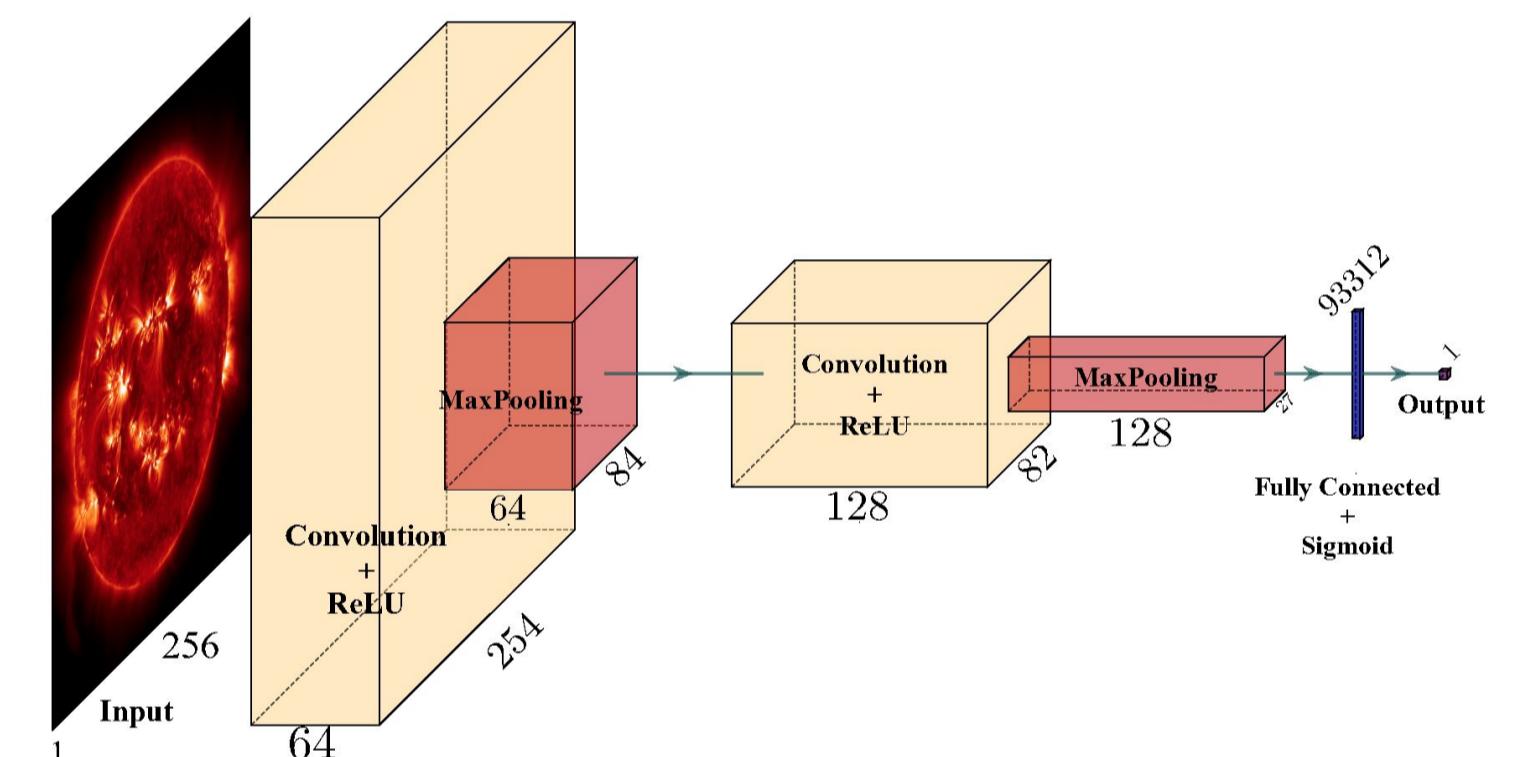
## Auto-calibration of the CCD sensitivity (A)

### RESULTS [7]

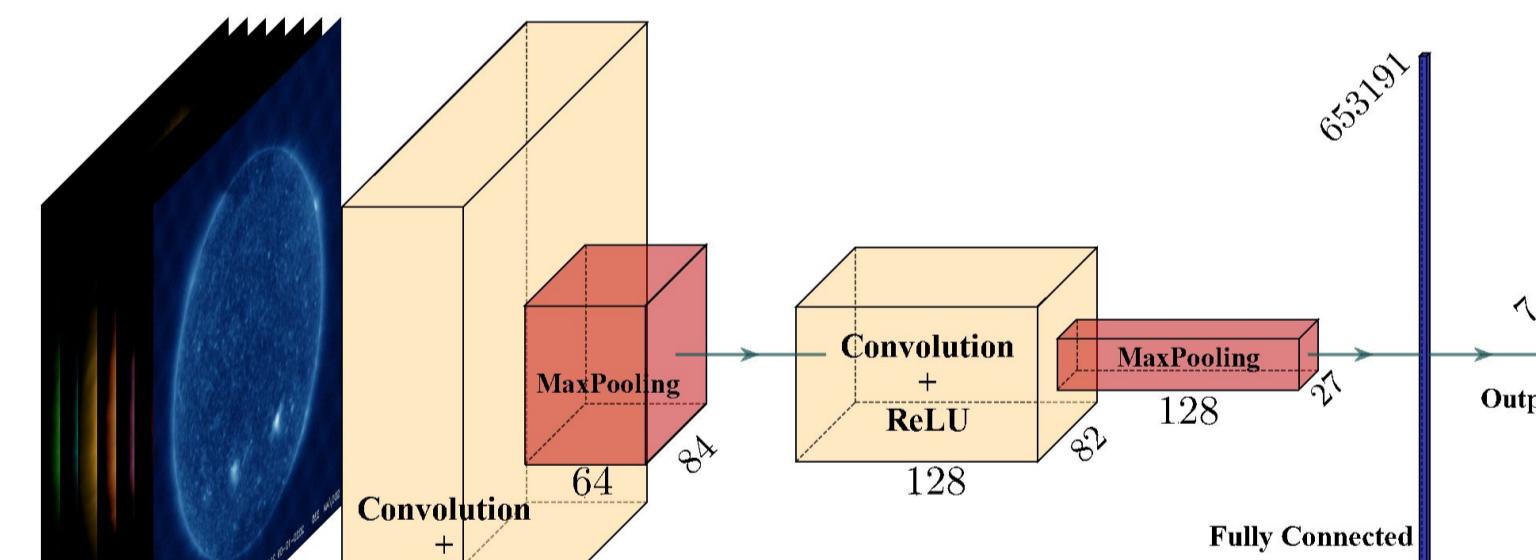


Predicted degradation curve from the single (dashed) and multi-channel (continuous) models for the different channels in comparison with the degradation curve from the sounding rockets measurements (V8, V9). The grey area is the uncertainty on the V9 calibration curve.

### CNN - SINGLE INPUT CHANNEL



### CNN - MULTIPLE INPUT CHANNEL



Model	Tolerances				
	0.05	5%	10%	15%	20%
Baseline	51%	27%	43%	56%	66%
Single Channel	78%	50%	73%	85%	92%
Multi Channel	85%	53%	77%	89%	94%

Results on the test set for the different approaches. The baseline is a non-machine learning method based on quiet areas of the Sun. Tolerance x% means the prediction is considered successful if the calibration error is within x%.

## APPLICATIONS

- ★ Enabling future HSO missions to auto-calibrate their EUV instruments without using sounding rockets.
- ★ Enabling Sun observatories from vantage points in deep-space (where sounding rocket calibration is not an option)

## DATA

We used pre-processed images from the SDOML dataset [3]

- downsampled to 512x512
- temporally aligned and spatially co-registered
- identical resolution (4.8 arcsec)
- corrected for instrumental degradation and exposure

In both the experiments we

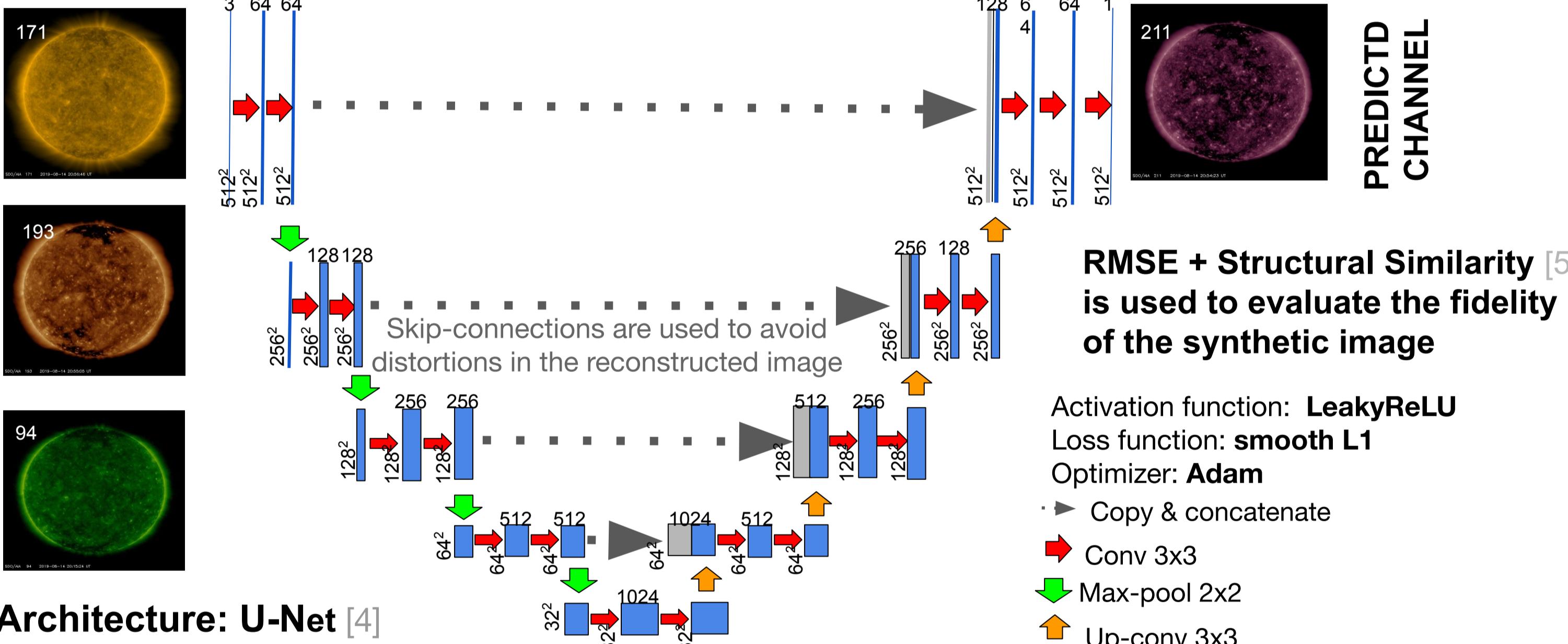
- split in train/test according to the month (to avoid solar cycle bias)
- span over several years of data

## COMMON IDEA

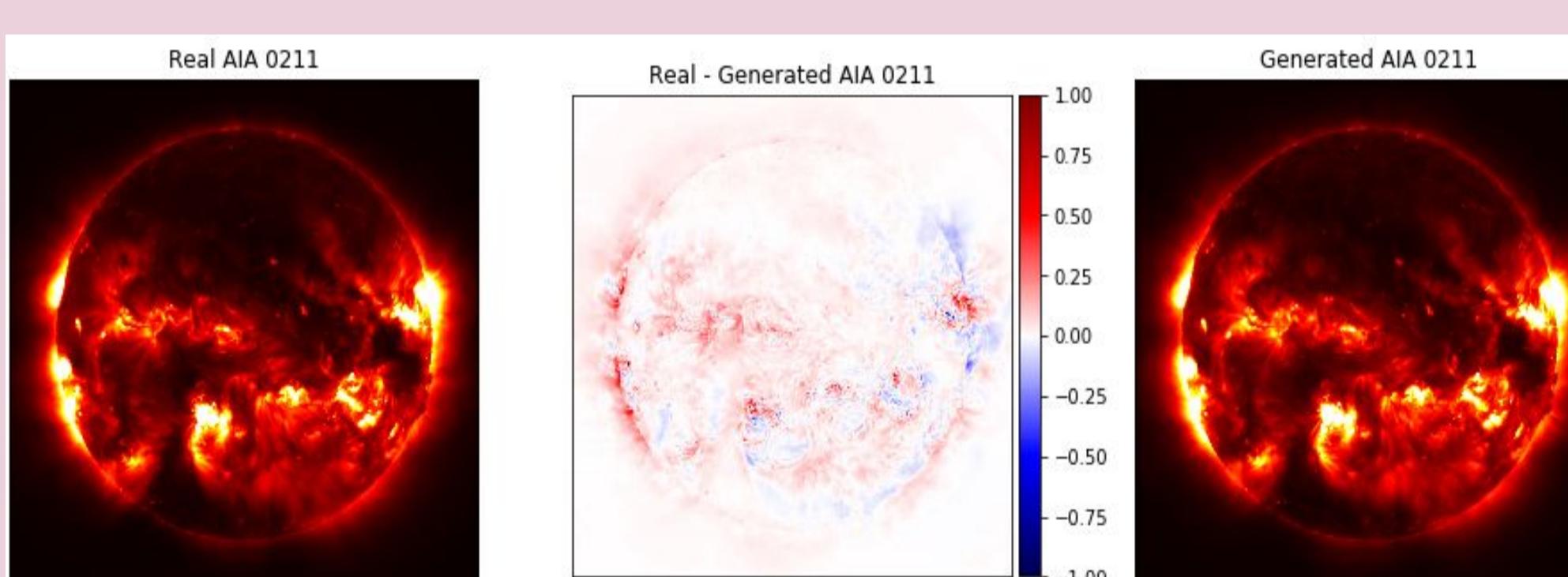
How the spatial features in the solar corona appear at different wavelengths is determined by physics. A neural network can learn the correlation between these features from previous images and use that for future predictions.

## Synthesis of Virtual Observations (B)

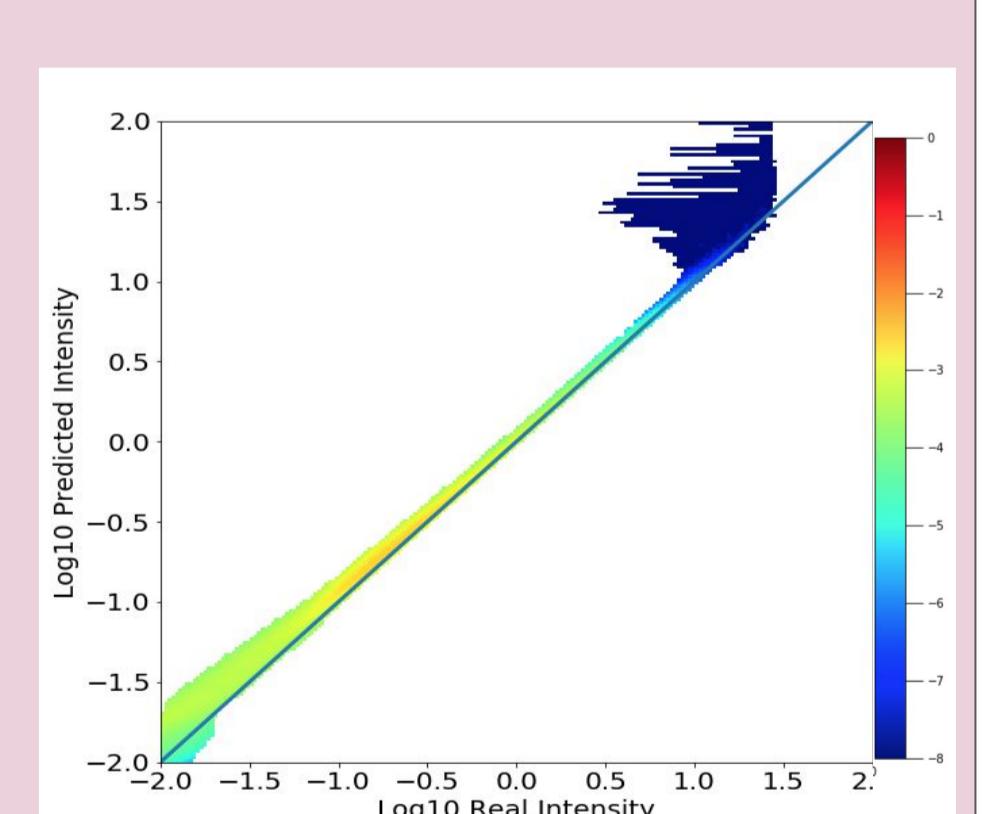
Image-to-image translation is used to generate a synthetic high-fidelity image of a missing channel



### RESULTS [6]



(Middle) Difference in units of data number/s/pixel between the real image (left) and the image reconstructed via **U-Net** (right).



Joint PDF at 90% c.l. for the test set on U-Net. Dark blue are extremely rare and saturated data points.

## APPLICATIONS

- ★ Reduction of **telemetry needs**, through the use of alternate data sources and later resynthesis.
- ★ Improved **reliability** against instrument channel failures. ★ **Enhanced observational capabilities**

[1] William Pesnell, Barbara Thompson, and Phillip Chamberlin. **The Solar Dynamics Observatory**. *solarphys*, 275:3–15, 11 2012. [2] J. R. Lemen et al. **The Atmospheric Imaging Assembly (AIA) on the Solar Dynamics Observatory (SDO)**. *Solar Physics*, 275:17–40, January 2012.

[3] Richard Galvez & al. **A Machine-learning Data Set Prepared from the NASA Solar Dynamics Observatory Mission**. *The Astrophysical Journal Supplement Series*, 242(1):7, May 2019. [4] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. **U-Net: Convolutional Networks for Biomedical Image Segmentation**. *LNCS*, 9351, 234–241. 10.1007/978-3-319-24574-4, 28, May 2015. [5] Zhou Wang et al. **Image Quality Assessment: From Error Visibility to Structural Similarity**. *IEEE Transactions On Image Processing*, 13(4):600–612, 2004. [6] Valentina Salvatelli, Souvik Bose, Brad Neuberg, Luiz F. G. dos Santos et al. **Using U-Nets to Create High-Fidelity Virtual Observations of the Solar Corona**, NeurIPS 2019 Workshop ML4PS, arXiv:1911.04006 [7] Luiz F. G. dos Santos, Souvik Bose, Valentina Salvatelli, Brad Neuberg et al. **Multi-Channel Auto-Calibration for the Atmospheric Imaging Assembly using Machine Learning** arXiv:2012.14023, to appear on A&A.